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AEN-PRO: Agent-based simulation tool for performance and working conditions assessment in production systems using workers' margins of manoeuvre

I. El Mouayni¹, A. Etienne¹, A. Siadat¹, J-Y. Dantan¹, A. Lux²

¹Laboratory of Design, Manufacturing and Control (LCFC), Metz, France

²National Institute of Research and Safety (INRS), Vandœuvre-lès-Nancy, France

Corresponding author's e-mail: ismail.elmouayni@gmail.com

Abstract: During the last eighty years, new work philosophies has been introduced and technological advancement changed radically the way of work, making it more reactive, agile but complex as well. As a result, classical approaches for production system design may no longer be sufficient to ensure productivity and safety of industrial systems. In the domain of occupational diseases, adopting a pure biomechanical approach, consisting in ensuring the non-violation of workers' biomechanical limits at each workstation is proved to be uncomplete. Beside biomechanical risk factors, psychosocial risk factors, which are strongly linked to the dynamic of the physical and informational flows, may contribute to the genesis of Musculoskeletal Disorders. By granting a certain workers' margins of manoeuvre, these risk factors can be limited. This article introduces AEN-PRO, a simulation tool for investigating the impact of physical flow on the production system and particularly workers, to assess their margins of manoeuvre and to ensure safer and productive systems.

Keywords: Human factors; Production systems; Occupational diseases; Simulation; Multi-agent systems

1. INTRODUCTION

In the last two decades, the work organizations especially industrial ones, have been through numerous changes. From Lean Manufacturing systems to agile and flexible cells, new forms of sociotechnical organizations were introduced in order to make production systems more efficient, more reactive, without losing productivity. Today technology makes this achievable. Whereas, in the domain of occupational diseases, Fewer improvements were made. It is undoubtable that new technologies helped significantly to integrate Human Factors (HFs) during design phases, by using advanced tools such as Human Digital Models (HDMs) and Virtual Reality (VR). These tools can be used to assess workstations and ensure the non-violation of biomechanical limits of the worker, based on evaluation systems such as Rapid Upper Limb Assessment (RULA) (McAtamney and Corlett, 1993), Ovako Working posture Analysis System (OWAS) (Karhu et al., 1977), or any other similar evaluation systems. However, except the powerful graphic engines or the fancy gadgets beneath these tools, the approach itself is still classical and seems uncomplete to ensure a full prevention against Work-related Ill Health (WIH) in modern manufacturing systems.

As a matter of fact, (Tuncel et al., 2008) reviewed different interventions in manufacturing that aim to reduce Musculoskeletal Disorders (MSDs), which represent the largest part of WIH reported in industry (European Agency for Safety and Health at Work, 2010) and found inconclusive results. Based on that, they suggested that both physical and nonphysical dimensions of working situation should be

assessed to ensure better prevention. Moreover, (Lanfranchi and Duveau, 2008) presented an epidemiological review which shows the relationship between Psychosocial Risk (PSR) factors, stress and MSDs. Examples of these factors are temporal pressure, workload, weak social support, monotony, combined with strong demands, lack of control and decisional latitude. As a result, different attempts were made in order to propose an approach for limiting the PSR factors. One of the noteworthy works, is the introduction of the concept of "worker's Margin of Manoeuvre" (MM) by several ergonomists (Caroly et al., 2010) as a way to limit the PSR factors and therefore, give a complementary prevention alongside the biomechanical one. However, this approach is limited for several reasons: First, it seems that there isn't any methodology for implementing MMs during the design phases. Usually, practitioners' intervention came after the establishment of the system, making it less efficient but never useless. Secondly, the approach itself is a reductionist one, since the practitioners make one-by-one workstation analysis. Whereas, the PSR factors highlighted before are strongly correlated with the physical and informational flow going through the whole system. Thus, using a holistic approach seems to be more promising. One of the techniques that could be used to achieve this, is the flow simulation.

Flow simulation have played a substantial role in evaluating the operational performance and the design of manufacturing systems (Negahban and Smith, 2014). Beside performance analysis, this paper aims to propose a simulation tool for working conditions assessment, as suggested by (Neumann and Medbo, 2009), using the MM concept. Accordingly, it is structured as follow: after introducing the concept of MM, the second section addresses the state of art regarding the

different attempts to address psychosocial aspects in production system using simulation. The third section presents in detail our proposition. The fourth one addresses a comparison between the tool predictions and experimental results. The last section is about discussion, conclusions and future work.

2. STATE OF THE ART

In this section, MM as a concept used to limit PSR factors is introduced, then a review of some noteworthy works which used simulation to address psychosocial aspects in production systems is given.

2.1 Work margin concept

There are two important positions regarding occupational diseases (Lanfranchi and Duveau, 2008). The first one considers that WIH are due to exposure to pathogenic external factors, including biomechanical and psychosocial ones. Based on that, the intervention of the practitioner consists in limiting these factors. The second approach considers that the one's health is a subjective matter, that the human is an organism full of subjectivity and needs to have a say on his environment by adapting it to his needs. Therefore, organizations with high level of constraints in terms of task planning, sequencing and sometimes, in terms of gesture are inconsistent with the human nature neither with the nature of work situation, full of variations itself. The concept of MM is based on the second position. It consists in establishing a certain level of work flexibility which gives the worker the possibility to adapt his way of working regarding the faced situation and with consideration to his health particularities (Durand et al., 2009). Thus, responding to the work demands and preserving his health by limiting risk factors and particularly psychosocial ones.

2.2 Approaches based on flow simulation

Most of WIH prevention approaches based on, Predetermined Motion Time Systems (Genaidy et al., 1989), biomechanical workload assessment systems (such as RULA and OWAS), DHMs or VR, consider one-by-one workstation assessment. However, the PSR factors highlighted in section 1 depend strongly on the nature of the physical and informational flow in the production system. For example, having a sudden variation on part arrivals flow may cause a stressful situation and a lack of visibility, both considered as PSR factors. Therefore, the whole structure of the system must be considered and its impacts on the different types of flows must be investigated. What is meant by "structure", is the interconnections between the different entities composing the production system and their spatial positioning (layout). Accordingly, (Neumann and Medbo, 2009) used a flow simulation to compare two configurations, a production line and a dual cell configuration with a parallel flow. In opposition to the first one, the parallel flow allows autonomous breaks, which is considered as a work flexibility given to the workers. The simulation gave a prediction of

productivity. As this one satisfies the management, the transformation toward dual cell configuration was allowed. Another interesting work is done by (Perez et al., 2014) which tried to evaluate the muscular fatigue of a worker in a workstation. This one depended on the entering physical flow. By simulating it, the level of fatigue at the investigated workstation was estimated. To integrate MMs during a production system design, (El Mouayni et al., 2016) proposed an agent-based simulation approach to evaluate both productivity and working conditions after establishing an organizational MMs. To assess the productivity, the use of the number of throughputs and among them rejected ones due to human errors is proposed. Regarding the working conditions, worker's fatigue and processing time are used to spot workstations with high level of workload and stress. The behaviors of production system entities are observed to assess the system's performance for improvement proposes using four Elementary States (ESs). Based on the last work, the next section introduces the proposed model for performance and working conditions assessment. The major extensions made since (El Mouayni et al., 2016) are in order to support temporal MMs integration.

3. PROPOSED MODEL FOR PERFORMANCE AND WORKING CONDITIONS ASSESSMENT

In this section, the model proposed for performance and working conditions assessment is discussed. The main objective is to present the model to the reader and to highlight the different extensions made. Accordingly, the main hypotheses of this work are stated, then the model is presented using two views. The first one is concerning the global structure used to model the production system. The second one is about the behavior modeling.

3.1 Model hypothesizes

The main problematic addressed in this article is the gap between the worker capacity and the work demands. Both variate due to several reasons. Human Factors (HFs) such as learning and fatigue impact worker's capacity. Similarly, different stochastic elements such as part arrivals, machine breakdowns, variable processing times, impact the physical and informational flow and therefore the work demands. By considering two main components: the physics and cognition, the worker's capacity is measured using the time needed to process the task T_{task} and the probability of success $P_{success}$ as given by (1):

$$[T_{task} \ P_{success}] = Function(S_{physics}, S_{cognition}) \quad (1)$$

Where $S_{physics}$ and $S_{cognition}$ are respectively the states of the physics and cognition of the worker. The physics are described by a fatigue index and its evolution due to external stressors. The cognition is about cognitive capacities regarding the task requirement but also includes internal representation of the environment depending on the visibility of the system. This last aspect is out of the scope of this work, which means that the proposed model is not valid for situations where visibility impacts the worker capacity by the

mechanisms of anticipation and adaptation. The main hypothesis of this work is considering that situations where the work demands (rate of entering parts) exceeds the worker capacity modeled by (1), leads to the PSR factors highlighted in the section 1. Based on that, the following model and indicators for assessing working conditions alongside with productivity is proposed.

3.2 Simulation conceptual model: Global structure

To model the production system, the conceptual model given in the figure 1 is proposed. The model is based on a multi-agent paradigm. Three types of agents are considered. Each of them has a behavior (AgentBehavior class) and a 3D geometric model (3Dmodel class). The first type of agent is the Moving Entity agent. It may represent any kind of entity that moves in the system such as parts, products and batches, which can trigger an agent behavior. The second type is the Mean agent which can be a machine, a Manual Workstation, a Stock or a Transfer Mean.

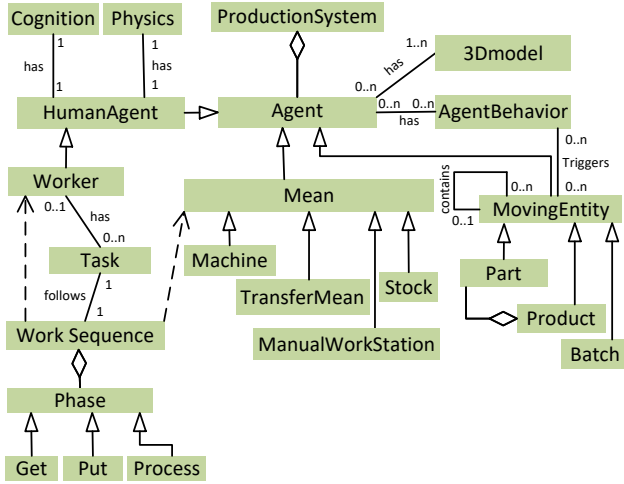


Fig. 1. Simulation conceptual model (UML class diagram).

The third type of agents is the Human agent. It is considered the new feature of this model in comparison with simulation models proposed in the literature. This agent has a physics module simulating the fatigue using (2) and (3) (Jaber et al., 2013):

$$F(t) = 1 - e^{-\lambda t} \quad (2)$$

$$R(\tau) = F(t)e^{-\mu \tau} \quad (3)$$

F is the fatigue index, λ and μ are respectively the fatigue and recovery rates, which need to be determined depending on the different factors that may induce fatigue, including the psychological stressors. $R(\tau)$ is the residual fatigue after a break of τ units of time. The second module is the cognition. It models the learning abilities of the human agent using (4) to (8) (Jaber and Bonney, 1997):

$$T_{n_i} = T_1(u_i + n_i)^{-b} \quad (4)$$

T_1 is the processing time corresponding the first execution (unexperienced worker), T_{n_i} is the processing time needed to produce n^{th} units during the cycle i (defined by a break or a

batch arrival). The parameter u_i is the experience at the beginning of the work cycle. The parameter b is calculated using (5):

$$b = -\frac{\log(LR)}{\log(2)} \quad (5)$$

Where LR is the learning rate measured in percentage. The term u_i is given by:

$$u_{i+1} = (u_i + n_i)^{1+f_i/b} (u_i + n_i + s_i)^{-f_i/b} \quad (6)$$

Initially, $u(i=1)=u_1=0$. The parameter s_i represents the number of units that would be produced during the cycle i if there wasn't a work break between the cycles. The parameter f_i represents forgetting rate. The parameters f_i and s_i are respectively given by (7) and (8):

$$f_i = \frac{b(1-b)\log(u_i + n_i)}{\log(1 + D/t(u_i + n_i))} \quad (7)$$

$$s_i = \left[\frac{1-b}{T_1} \tau_i + (u_i + n_i)^{1-b} \right]^{1/(1-b)} - (u_i + n_i) \quad (8)$$

The term τ_i refers to the break duration at the end of the cycle i . D is the time for total forgetting, $t(u_i + n_i)$ is the time needed to produce $u_i + n_i$ units continuously (without breaks). The agent Worker inherits its properties from the HumanAgent class, including the cognition and physics modules. Several tasks can be associated to each worker (the task executed is decided based on the received moving entity). Each task follows a Work Sequence, which is a sequence of ordered Phases, typically, a Get, a Put and a Process phase. The Work Sequence and the Phases are addressed in detail in the section 3.4. They are the main extension of the previous model. The class AgentBehavior was also improved by using the Finite State Machine (equivalent to finite state automaton) provided by jade library (Jade, 2015) instead of using cyclic behavior (see (El Mouayni et al., 2016)). In the following section, the behavior modeling is presented.

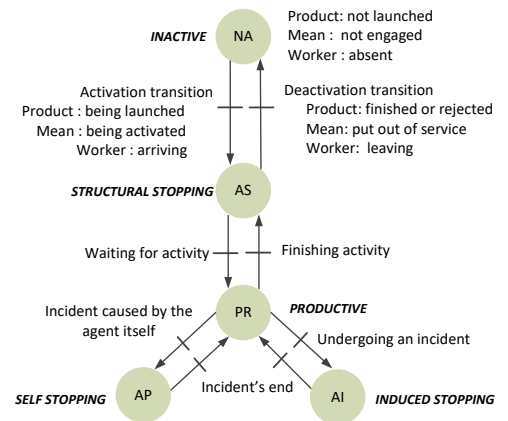


Fig. 2. Behavior modeling using finite state automaton.

3.3 Conceptual simulation model: Agents' behaviors

To model the agents' behaviors, a finite state automaton is used with four Elementary States (ESs): structural stopping AS, productive PR, induced stopping AI and self-stopping

AP state. The AS state is entered when an agent stopping is caused by the structure of the system, such as a product waiting in a queue or a machine waiting for a busy worker. The PR state is entered when all conditions for executing the main function or role of the agent are satisfied. The AI state is entered when the agent stops playing its role due to an external event caused by another agent. Finally, the AP state is entered due to an internal event such as a machine stopping when it breaks down or a worker taking a break (figure 2). Using simulation, the ESs distribution regarding each agent can be generated and by analyzing it, the performance of each one of them can be assessed.

3.4 Worker's productive state: Underlying model

When the Worker enters the productive state, he starts executing the task following a Work Sequence. At this stage, only assembly tasks are addressed. However, the model can be extended by adding other Phases such as Machine Setting phase or Tool Changing phase to model machining operations. The proposed sequence is based on Maynard Operation Sequence Technique (Genaidy et al., 1989) and focuses on part transfer as shown in figure 3. The work sequence is composed by five phases, a Get phase (Gt), a Put phase (Pt), a Process phase (Pr), then a Get and a Put phase. Executing these phases induces a fatigue rise with different fatigue rates depending on the conditions of each one.

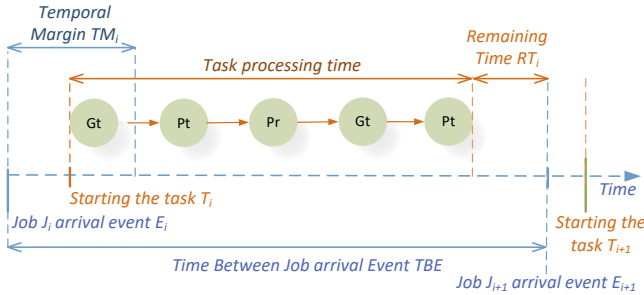


Fig. 3. Work sequence model.

The Process phase execution time is determined using (4). This phase induce a fatigue and learning rise and depending on the level of these factors, the worker may make an error with a Human Error Probability (HEP) modeled by (9) (Givi et al., 2015). The parameter F is the fatigue index given by (2), T_x is processing time reached by gaining experience, T_1 is the processing time without any experience at all. w_1 and w_2 are respectively the weight of fatigue and learning in the error occurrence; Their sum is equal to 1. α is for scaling the HEP depending on the task difficulty.

$$HEP = (w_1 \cdot F + w_2 \cdot \frac{T_x}{T_1})^\alpha \quad (9)$$

To determine the execution time of the Put and Get phases, an underlying model is constructed as shown in the figure 4. The Get phase is decomposed into three “sequence elements”: Action distance (A), a Body motion (B) and a Gain control (Gc) sequence element. The element A represents a horizontal movement. It is simulated by changing the position of the worker and advancing the

simulation clock by the travel time. The element B represents a vertical movement such as the worker bending to pick a product. At this stage, this element is neglected in comparison with A element. Otherwise, model for human gesture are needed to estimate time needed for B element execution. The Gaining control (Gc) element represents the worker grasping a product and its time execution is also neglected. Likewise, the Put phase is composed by A, B and Placement element (Pl), which represents the worker placing a product.

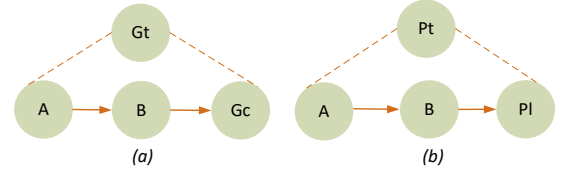


Fig. 4. Get (a) and Put (b) phases decomposition.

In the work sequence model shown in the figure 3, two parameters are highlighted and are related to the task flexibility and thus, to the worker's MM: Temporal margin of Manoeuvre TM and Remaining Time RT . TM represents the maximum delay time the worker can have before processing the task and without having a flow clogging. If we consider the average Time Between job arrival Events $MTBE$ and the mean in which, the moving entities are stocked before getting processed by the worker, TM can be estimated using (10):

$$TM_i = (b_c - b_i) \cdot MTBE_i \quad (10)$$

Where b_c is the mean's buffer capacity used for the Get phase and b_i its current size. The RT parameter is calculated by subtracting the instant of finishing the work sequence from the next job arrival event instant. This parameter is for measuring the capacity of the worker to execute the task within the time between two job arrivals. Having a RT positive indicates that there is no need for flexibility ($TM = 0$). Otherwise, if $RT < 0$, the worker needs a positive TM to be able to postpone the next task the time needed to finish the previous one. If $RT = 0$, TM gives the worker time for relaxation and fatigue recovery if needed, based on his own initiative. Having $RT < 0$ and $TM = 0$ represents a stressful situation where the work demands exceed the worker's capacity without giving him enough flexibility.

The conceptual model presented above is implemented using java programming language and Jade library. Jade has different packages for multi-agent system development. Other functionalities were added like a graphic engine and a Graphic User Interface GUI. The tool obtained is called AEN-PRO (Agents-based ENGINE for PROduction system simulation). The implementation model and other technical aspects related to the simulation technique used are not detailed in this article.

4. EXPERIMENT

In order to have a first validation of the developed tool, an experiment was conducted. A specific experimental bench was designed by INRS (National Institute of Research and Safety) as shown in figure 5. The results of the experiment

were published in (Claudon et al., 2016), which are about to be reused for the tool validation. The experimentation only proves the tool validity regarding the bench configuration. Other experiments with various configuration need to be performed to claim the validity of the proposed tool. However, only white-box validation is needed as the basic components of the model (fatigue, learning and task sequence) are based on valid literature.

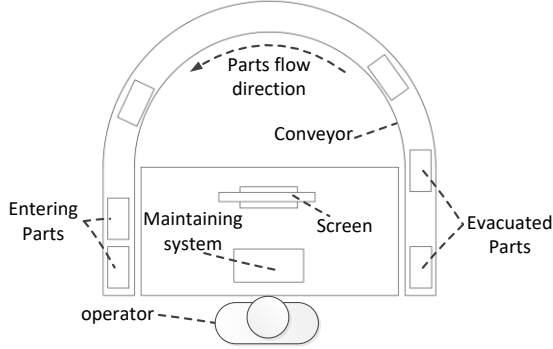


Fig. 5. Experimental bench.

The bench is composed by a conveyor ensuring the parts transfer. When the operator finishes processing a part, he puts it in the right side of the conveyor to be transferred to the left one. The transfer follows a specific pattern in order to reproduce a real physical flow pattern. To process the part, the worker puts it in a maintaining system and processes it as follow: 1) putting five pawns into the appropriate holes in a correct order, 2) An option consists in putting a sixth pawn, 3) Applying a force using a lever action, 4) Removing the pawns, 5) Putting the part in the conveyor for transfer. The screen shows the progression of the task (the pawns installed or removed, the level of force applied) and to indicate if the current part has an option (six pawns to install). The experiment is conducted during 100min, the work is paced and a part arrives every 21s. The conveyor speed is set to 0.25 m.s^{-1} and only three parts are allowed to be stocked ($b_c=3$) along the conveyor.

Regarding AEN-PRO parameters settings, the table 1 gives the fatigue rate values corresponding to the different phases. The recovery rate (μ) is set to $13.17 \times 10^{-2} \text{ min}^{-1}$. These values were determined by making a mapping with Peter and Steel partner's fatigue allowances determination tables appeared in (Kanawaty and International Labour Office, 1992).

Table 1. Fatigue accumulation parameters

Phase	Get	Process	Put
$\lambda \text{ (} 10^{-2} \text{ min}^{-1} \text{)}$	2.15	2.24	2.12

For the learning parameters, T_l is set to 0.9min (observed during the experiment), LR is set to 0.8 (medium learning capacity) and D is considered equal to one month. Regarding the HEP model, α is set to 1.0 using a mapping with values given by the HEART method (Kirwan, 1996), w_1 and w_2 were set both to 0.5 considering that fatigue and learning have the same impact in the error occurrence.

The table 2 gives the comparison between the simulation outputs and the experimental results in terms of throughputs

and rejected parts numbers. The figure 6 shows the task processing time variation according to AEN-PRO and to the experiment. Figure 7 shows the TM variation, the figure 8 describes the RT variation and the figure 9 gives the worker and conveyor (transfer mean) ESs distribution.

Table 2. Processed and rejected parts numbers

Results	Experiment	AEN-PRO	Error
Throughputs	217	200	7.8%
Rejected parts	19	17	10.5%

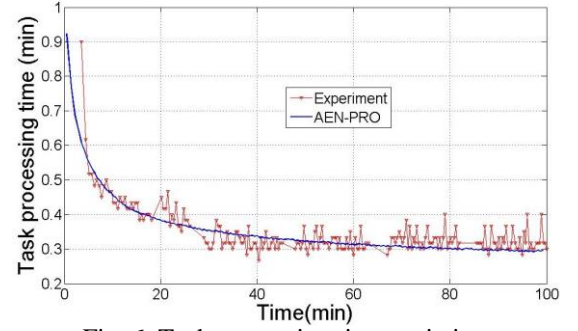


Fig. 6. Task processing time variation.

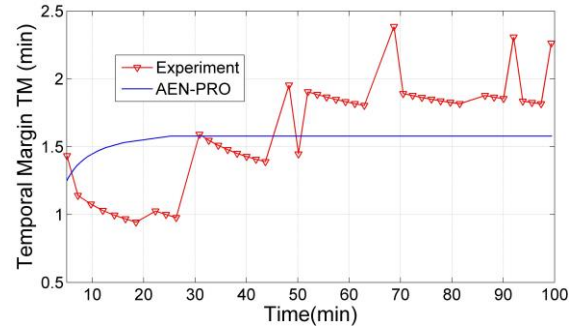


Fig. 7. Temporal Margin (TM) variation.

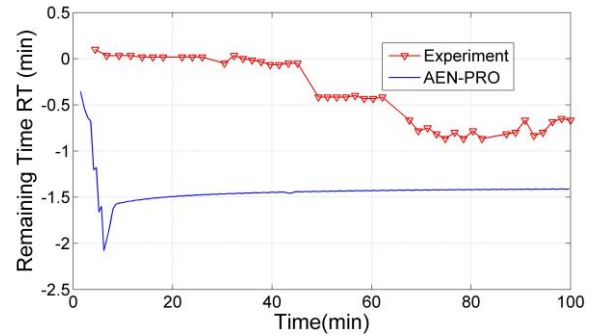


Fig. 8. Remaining Time (RT) variation.

5. CONCLUSIONS AND DISCUSSION

This article introduces an agent-based tool (AEN-PRO) for production system simulation. The main objective is to assess both, the productivity and the working conditions. The first is assessed by estimating the number of processed parts, among them the rejected ones due to human errors. Regarding the working conditions assessment, beside fatigue index distribution, two other parameters were introduced: Temporal margin of Manoeuvre (TM) for assessing the flexibility of a task and the Remaining Time (RT) for evaluating the

consistency between the worker capacity and the work demands. Using these two parameters, potential PSR factors can be identified. To find improvements leads, performance is assessed by observing Elementary States (ESs) distribution regarding each agent.

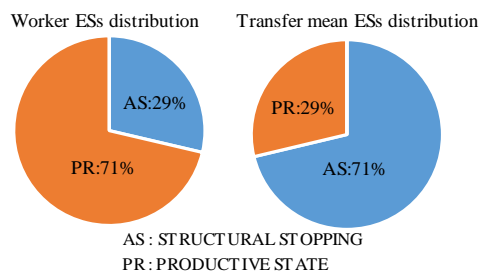


Fig. 9. Worker and transfer mean ESs distribution.

In the fourth section of this article, an experiment was conducted in order to validate the tool. The table 2 shows the throughputs and rejected part numbers obtained using the experiment and AEN-PRO. The estimation error doesn't exceed 10.5%. The figure 6 shows that a high level of precision regarding task processing time prediction is achieved using AEN-PRO, but also highlight the presence of stochastic variations in the real task processing time. These variations are not supported by the introduced work sequence model, which is rather deterministic. In the other hand, they impact significantly the *TM*. However, the *TM* approximation given by AEN-PRO still good as the error is around 30% at worst. Regarding the parameter *RT* (figure 8), at first, diversion between the AEN-PRO estimation and the experimental results at the beginning of the job execution is noticed. This is mainly due to the parts arrival. In AEN-PRO, the work was paced from the beginning with a part arrival each 21s, exceeding the worker capacity and causing the drop of *RT*. In the experiment, the work was rhythmized at the beginning according to the worker capacity and as this one gains deftness, the work became paced, causing simulated *RT* and experimental one to converge.

The figure 9 shows the worker's and the conveyor (transfer mean) ESs distribution, which can be used to make subtle assessment regarding productivity and not to limit to the classical throughputs. The diagram shows a certain level of structural stopping (AS), which indicates that there is room for improvement. Combining this with the analyze of the parameters *RT* and *TM*, gives the manufacturing system designer, a tool to assess both productivity and working conditions and can be used to assess larger systems and if needed, to improve its whole structure and not to limit to local improvement.

With the development of AEN-PRO, the opportunity of introducing a tool-centered methodology for production system improvement is given. The perspectives also include simulation model extensions in order to support other aspects, related to the job nature such as modeling other types of operations (machining, inspection or maintenance operations), aspects related to HFs such as stochastic processing times (beside the impact of learning) and worker's adaptability and anticipation, or aspects concerning the nature

of organization such as rotations and collaborations. These are some leads for the future works.

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